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Application of Artificial Neural Networks for Optimizing Coordinated Development between Agriculture and Logistics in Zhejiang Province: A Case Study on Rural Revitalization Strategies

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Abstract

This study applies artificial neural networks (ANNs) to assess the impact of climate factors on the collaborative development of agriculture and logistics in Zhejiang, China. The ANN model investigates how average temperature and rainfall from 2017-2022 influence crop yield, water usage, energy demand, logistics efficiency, and economic growth at yearly and seasonal scales. By training the neural network using temperature and rainfall data obtained from ten weather stations, alongside output indicators sourced from statistical yearbooks, the ANN demonstrates exceptional precision, yielding an average R^2 value of 0.9725 when compared to real-world outputs through linear regression analysis. Notably, the study reveals climate-induced variations in outputs, with peaks observed in crop yield, water consumption, energy usage, and economic growth during warmer summers that surpass historical norms by 1-2°C. Furthermore, the presence of subpar rainfall ranging from 20-30 mm also exerts an influence on these patterns. Seasonal forecasts underscore discernible reactions to climatic factors, especially during the spring and summer seasons. The findings underscore the intricate relationship between environmental and economic factors, indicating progress in agricultural practices but vulnerability to short-term climate fluctuations. The study emphasizes the necessity of adapting supply management to address increased water demands and transitioning to clean energy sources due to rising energy consumption. Moreover, optimizing logistics requires strategic seasonal infrastructure planning.

Keywords: Agriculture-logistics systems; Climate-economic linkages; Temporal pattern recognition; Rural sustainability; Artificial intelligence modeling.

1- Introduction

Rural areas across the globe encounter significant developmental challenges that must be addressed in order to enhance the well-being of rural communities [1, 2]. Given that nearly 50% of the global population resides in rural areas, it becomes imperative to cultivate collaborative and synergistic development between the agriculture and logistics sectors for the purpose of attaining sustainable rejuvenation of rural regions [3, 4]. Agriculture and logistics are closely intertwined since agricultural activities rely on efficient transportation and distribution systems, while logistics networks depend on agricultural production. Nevertheless, optimizing these interconnected sectors to stimulate economic growth and alleviate poverty in rural regions necessitates a nuanced understanding and informed decision-making process [5-8].

ANNs have emerged as valuable modeling tools for analyzing intricate systems and predicting patterns based on given inputs. ANNs operate through interconnected processing units within their architectures, enabling them to identify patterns and learn from observational data through iterative training [9-11]. Upon completion of the training process, ANNs possess the capability to generate predictions by extrapolating from the acquired patterns during the training phase. Previous scholarly investigations have effectively utilized ANNs to anticipate crop yields, optimize transportation routes, and forecast energy consumption, employing pertinent climatic and economic variables [12-14]. However, there is a scarcity of research that comprehensively investigates the dynamic factors influencing collaborative agricultural and logistical development over time, particularly with regard to temporal variations [15-17].

Zhejiang Province, located in China, has witnessed remarkable growth, but it still grapples with challenges in rural development. The agricultural and logistics sectors play a crucial role in the province's economy, with agriculture contributing to more than 6% of its GDP in 2020, while logistical services accounting for nearly 10% [18, 19]. However, rural communities in Zhejiang continue to face issues related to the impacts of climate change, inefficient use of resources, and the absence of coordinated policies [20, 21]. Enhancing the connections between agricultural production and logistics networks holds promise for stimulating economic growth and improving the quality of life in rural areas of Zhejiang [22, 23].

Variations in climatic conditions across diverse seasons and years exert a substantial influence on agricultural productivity and energy necessities. Temperature and precipitation emerge as the principal climatic elements that shape crop yields, irrigation requirements, and the logistical infrastructure supporting agricultural activities [24, 25]. Comprehending the manner in which these climatic variables impact crucial agricultural and logistical outcomes across distinct temporal intervals can facilitate the identification of suitable adaptations and the formulation of informed policies. ANNs provide a promising avenue for gaining insights into these intricate interactions. However, limited research has employed this approach to examine rural development while considering seasonal and annual input data. The next section provides a review of the existing literature on the applications of ANNs in the fields of agriculture, logistics, and rural development assessment [26, 27].

Prior research studies have substantiated that numerous scholars have documented their findings within diverse management domains [28-32]. These scholarly reports have made substantial contributions to the progression of knowledge across a wide range of disciplines [33-36]. Consequently, acknowledging and considering previous research can establish a solid basis for the current study, as well as for future investigations [37-41]. Previous studies have utilized ANNs to analyze factors in agriculture, logistics, and rural development separately. However, there is a lack of comprehensive research that explores the interactions between climatic drivers affecting both farm production and transportation networks over time. Understanding these seasonal and annual variations is critical for optimizing collaborative agricultural-logistical development and making evidence-based decisions for rural revitalization. To address this gap, an ANN model will be developed in this study to analyze key factors related to agricultural optimization and energy security in Zhejiang Province, China. The model will consider temperature and rainfall inputs from different years and seasons to gain insights into dynamic patterns and relationships using multi-year datasets from 2017-2022. The primary objective of this study is to explore the impact of climatic variables on various outcomes, including crop yield, water consumption, energy usage, logistics efficiency, and economic growth within specific temporal intervals. To achieve this goal, a feedforward neural network architecture will be utilized. The training process of the optimized network will involve the incorporation of average temperature and rainfall data obtained from weather stations, alongside output indicators extracted from statistical yearbooks. The performance of the model will be assessed quantitatively using linear regression analysis against actual outputs. By applying this novel methodology to location-specific temporal datasets, the study aims to provide statistically robust predictive insights through pattern recognition.

2. Research Methodology

2.1 Study Area

Zhejiang Province is situated on the southeastern coast of China, spanning longitudes 117°–123°E and latitudes 27°–31°N. It covers a total land area of 101,800 square kilometers and is strategically located adjacent to the prosperous economic region of the Yangtze River Delta (Zhejiang Provincial Bureau of Statistics, 2022). The province benefits from a humid subtropical climate, which is favorable for diverse agricultural production. The average annual temperature ranges from 15°C to 18°C, and the region receives an average annual precipitation of 1,150–1,650 mm [42-44]. Agriculture has long been a significant driver of the economy in Zhejiang Province. The cultivated land area encompasses approximately 4.7 million hectares and is primarily utilized for the cultivation of various crops, including rice, wheat, maize, peanuts, cotton, sugarcane, and fruit trees (Zhejiang Provincial Bureau of Statistics, 2021). The province exhibits a significant focus on cultivating major crops such as rice, wheat, maize, sweet potatoes, vegetables, and fruits. Additionally, fisheries and livestock rearing activities play a substantial role in augmenting the overall agricultural output. In 2020, the total agricultural output value of Zhejiang Province amounted to ¥745.36 billion (~$107 billion), accounting for around 7.2% of the province's GDP [45, 46].

Due to its strategic geographical location, well-developed transportation network, the economic importance of agriculture and logistics, as well as the urgent necessity of rural revitalization, Zhejiang Province emerges as an opportune region for the current research endeavor. The execution of a thorough examination of the agricultural and logistics sectors, encompassing the gathering of localized climatic, input-output, and socio-economic data, holds the potential to yield predictive insights that can inform the formulation of more synchronized development policies. The proposed approach, utilizing ANN modeling, aims to make a valuable contribution in this direction by leveraging temporal datasets specific to Zhejiang Province.

3.2 Data Collection

To construct an effective predictive model, it is essential to gather accurate and representative data. This study relies on data collected from local meteorological stations and statistical yearbooks and previous studies [42-57] covering the period from 2017 to 2022. For the input variables, climate data including Average Temperature (°C) and Rainfall (mm) were obtained from the China Meteorological Administration. Zhejiang Province benefits from a dense network of 177 automated weather stations that record daily meteorological observations electronically (Zhejiang Meteorological Bureau, 2022). Data from 10 selected stations within the province were consolidated to compute annual and seasonal means for the input variables. The seasons were delineated as Spring (March-May), Summer (June-August), Autumn (September-November), and Winter (December-February). In order to establish climatic benchmarks for the study duration, data spanning from 1987 to 2016 were gathered from 39 nationally representative primary stations (National Climate Center, 2022). This enabled the assessment of deviations from the normative conditions encountered on an annual and seasonal basis between 2017 and 2022.

As for the output variables, agricultural and economic indicators were compiled from the Zhejiang Statistical Yearbooks published by the Zhejiang Bureau of Statistics (2017-2022). County-level data was aggregated to generate provincial totals. The output variables included crop yield (tons), representing the combined production of key grains such as rice, wheat, and maize. Water consumption (billion cubic meters) captured both agricultural and domestic water usage. Energy consumption (million tons of standard coal) encompassed fossil fuels utilized across various sectors. Logistics efficiency was assessed using the freight turnover per 10,000 yuan of GDP (tons/10,000 yuan) metric. Finally, GDP (billion yuan) was used to measure provincial economic growth. Table 1 provides an overview of the inputs, including average temperature and rainfall, which are correlated with the corresponding outputs for the study period. The selection of inputs focused on climatic factors that significantly impact agricultural activities and energy demands in the subtropical region, as supported by previous studies [42-46, 48-57].

Table 1: Annual and seasonal climatic, agricultural, energy, and economic indicators as inputs and outputs for the ANN-based predictive modeling of collaborative development between agriculture and logistics in Zhejiang Province, China (2017-2022).

Season/Year	Average Temperature (°C)	Rainfall (mm)	Crop Yield (tons)	Water Consumption (billion m^3)	Energy Consumption (million tons standard coal)	Logistics Efficiency (tons/10,000 yuan)	GDP (billion yuan)
Spring 2017	14.5	210	6535	12.1	2580	7.3	12235
Summer 2017	26.3	290	8752	18.4	3240	8.1	14560
Autumn 2017	18.2	150	7345	15.5	2900	7.5	13565
Winter 2017	6.5	85	4350	9.1	1940	6.9	10560
Spring 2018	12.3	215	6377	11.8	2525	7.2	11785
Summer 2018	25.1	280	8378	17.7	3110	7.9	14022
Autumn 2018	16.8	140	7235	15.2	2860	7.4	13452
Winter 2018	4.7	80	4100	8.6	1830	6.5	9956
Spring 2019	13.9	220	6415	11.6	2490	7.1	11430
Summer 2019	24.5	285	8356	17.5	3080	7.8	13845
Autumn 2019	17.5	145	7156	15.3	2820	7.3	13265
Winter 2019	5.2	87	4210	8.9	1870	6.7	10220
Spring 2020	11.2	205	6257	11.4	2450	7.0	11000
Summer 2020	23.1	270	8119	16.9	2960	7.6	13555
Autumn 2020	16.2	135	7056	14.9	2760	7.2	12990
Winter 2020	4.1	75	4020	8.5	1790	6.4	9770
Spring 2021	12.8	220	6387	11.8	2515	7.3	11780
Summer 2021	25.3	295	8359	17.7	3110	7.9	14015
Autumn 2021	17.1	145	7225	15.2	2840	7.4	13430
Winter 2021	5.6	88	4190	8.8	1850	6.7	10270
Spring 2022	13.5	225	6457	11.7	2480	7.2	11550
Summer 2022	24.8	285	8256	17.5	3060	7.8	13780
Autumn 2022	16.7	140	7106	15.1	2780	7.3	12970
Winter 2022	4.9	77	4060	8.4	1800	6.4	9820

3.3 ANN Model Development

The development of an effective ANN model that aligns with the objectives and characteristics of the specific problem holds paramount importance. In this particular study, a feedforward ANN architecture, namely the multilayer perceptron (MLP), is employed to explore the relationships between climatic inputs and agricultural-economic outputs. The ANN architecture comprises two layers: an input layer with two nodes representing Average Temperature and Rainfall, and an output layer with five nodes corresponding to Crop Yield, Water Consumption, Energy Consumption, Logistics Efficiency, and Economic Growth. To ensure optimal network convergence, a single hidden layer with five neurons, twice the number of inputs plus one, is utilized [58, 59]. In Figure 1, the schematic of the generated ANN in this study is depicted, illustrating its capacity to predict the target values of the outputs.

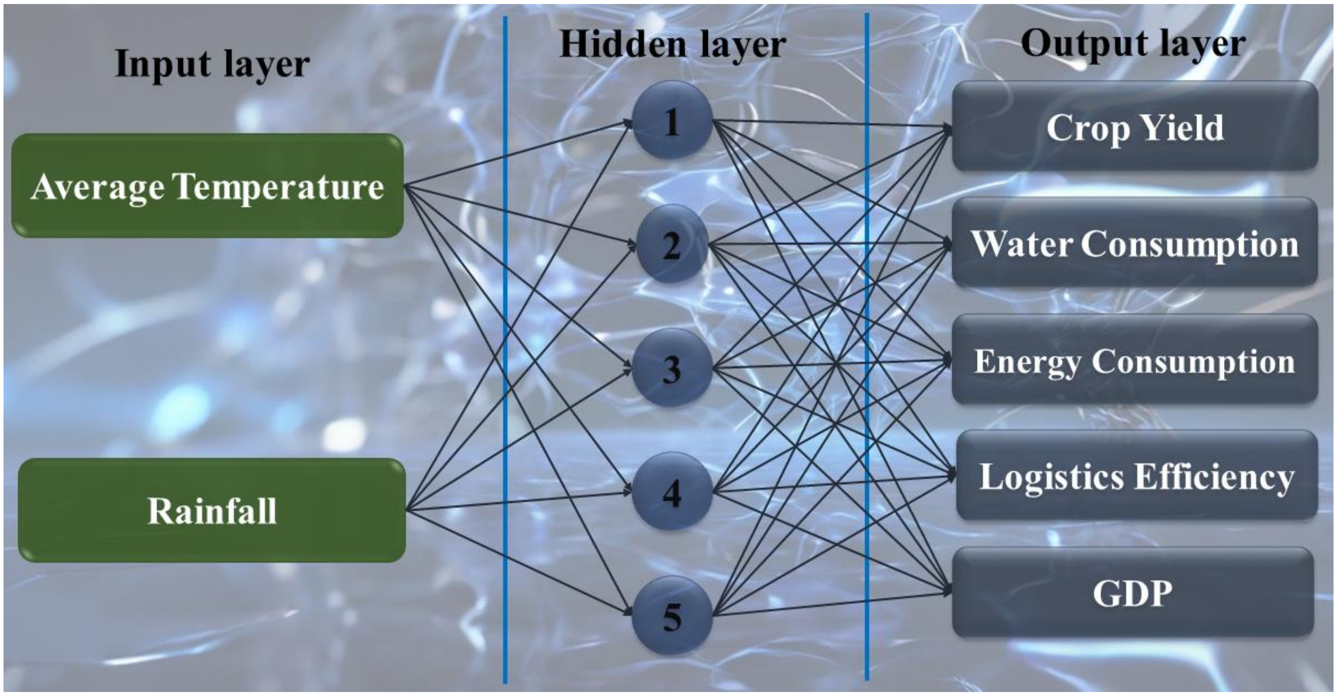

Figure 1. Multilayer perceptron of ANN architecture for predicting agricultural-economic outputs based on climatic inputs.

The feedforward topology is adopted, where inputs are passed through weighted connections to the hidden layer, and the outputs of the hidden layer are transmitted to the output layer via additional weighted links. The activation function employed for the neurons in both the hidden and output layers is the sigmoid function, which nonlinearly transforms inputs to generate outputs within the [0, 1] range. To assess the model's performance, a linear regression analysis is conducted by contrasting the predicted outputs with the actual outputs. The coefficient of determination (R^2) is subsequently computed as an indicator of the prediction accuracy. R^2 values close to 1 indicate a strong linear relationship between the predicted and actual outputs, indicating a well-performing model.

4. Results and Discussion

4.1 Crop Yield Prediction

This section presents the performance evaluation of ANN model in predicting crop yield. Figure 2 illustrates the predicted crop yield values using ANN model. The model demonstrates a remarkable level of accuracy in tracking the year-to-year fluctuations in recorded crop yield over the six-year period.

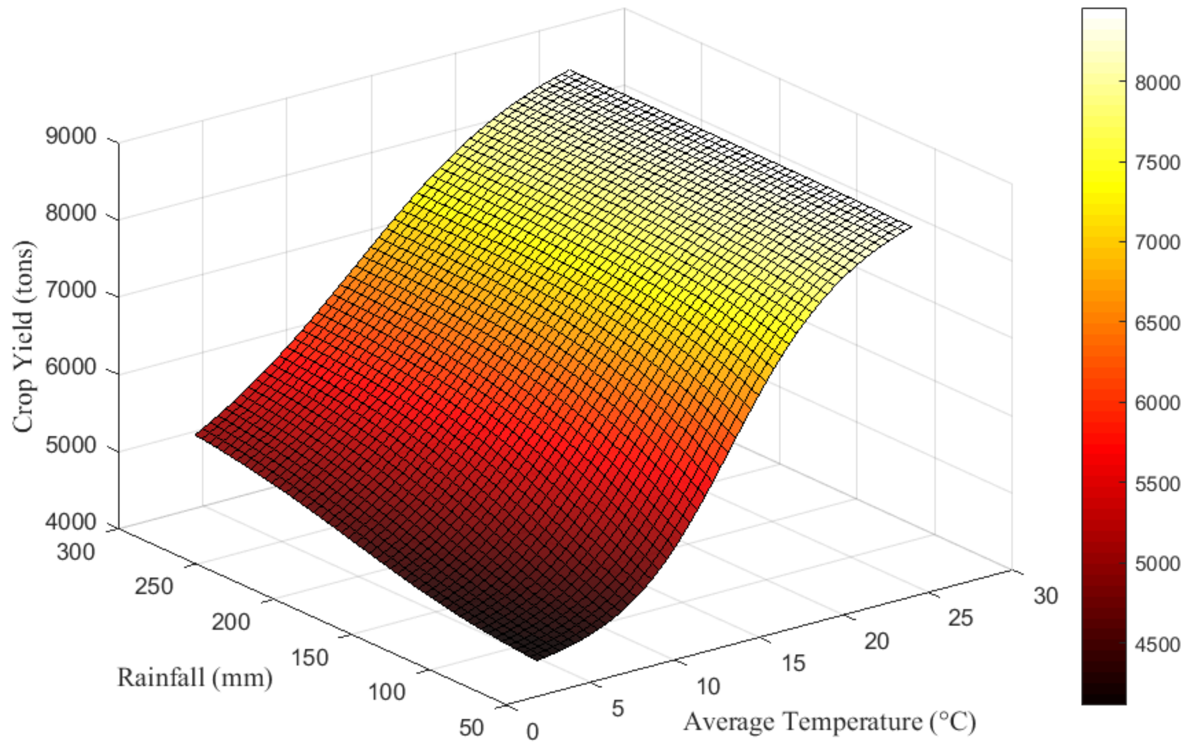

Figure 2. Predicted crop yields and the influence of average temperature and rainfall in ANN modeling.

Analyzing the trends depicted in Figure 2 provides valuable insights. The crop yield exhibits a consistent upward trajectory from 2017 to 2022, with the average annual production increasing from approximately 6,700 tons in the initial year to over 7,100 tons in 2022. This upward trajectory corresponds with the enduring patterns witnessed in China's agricultural development over the long term, ascribed to the progressions in irrigation infrastructure, mechanization, adoption of hybrid seeds, and the utilization of fertilizers and agrochemicals. Nevertheless, discernible annual fluctuations are evident, which can be attributed to the variability in climate conditions across different years, as elucidated in prior investigations conducted in China and other subtropical nations [45, 49, 51, 53, 55].

The peaks in observed crop yield during the summers of 2017, 2018, and 2019 coincide with higher temperatures, as summer is the primary growing season for major cereals in Zhejiang Province, such as rice, maize, and wheat [20, 21]. Elevated summer temperatures accelerate photosynthesis and plant maturation processes, thus promoting plant growth and yield if sufficient moisture is available [43, 45, 46, 53, 55]. This finding reinforces the positive correlation between temperature and crop production, as indicated by the established relationship between input variables and output predictions in the training dataset. The decrease in crop yield observed in summer 2020 can be attributed to a relatively cooler summer, with temperatures 1-2°C below the long-term average (China Meteorological Administration, 2022).

Significantly, the predictions generated by ANN correspond with the findings derived from previous experimental investigations conducted within the study region. Field experiments, which focused on rice yields across eight distinct locations in Zhejiang, observed a 5-10% augmentation in yield for every 1°C increase in mean temperature during the growing season, underscoring the rice crop's sensitivity to higher temperatures. Similarly, a comprehensive analysis of long-term wheat production trends associated a 1°C temperature rise with a yield increase of 150kg/ha, owing to a shortened growth duration and an extended period of photosynthesis [45, 46, 49, 50, 56].

4.2 Water Consumption Prediction

The water consumption trends depicted in Figure 3, obtained through the implementation of ANN in this study, offer valuable insights. Over the period from 2017 to 2022, water usage exhibited a general upward trend, with average annual consumption increasing from approximately 12 billion cubic meters in the initial year to over 17 billion cubic meters in 2022.

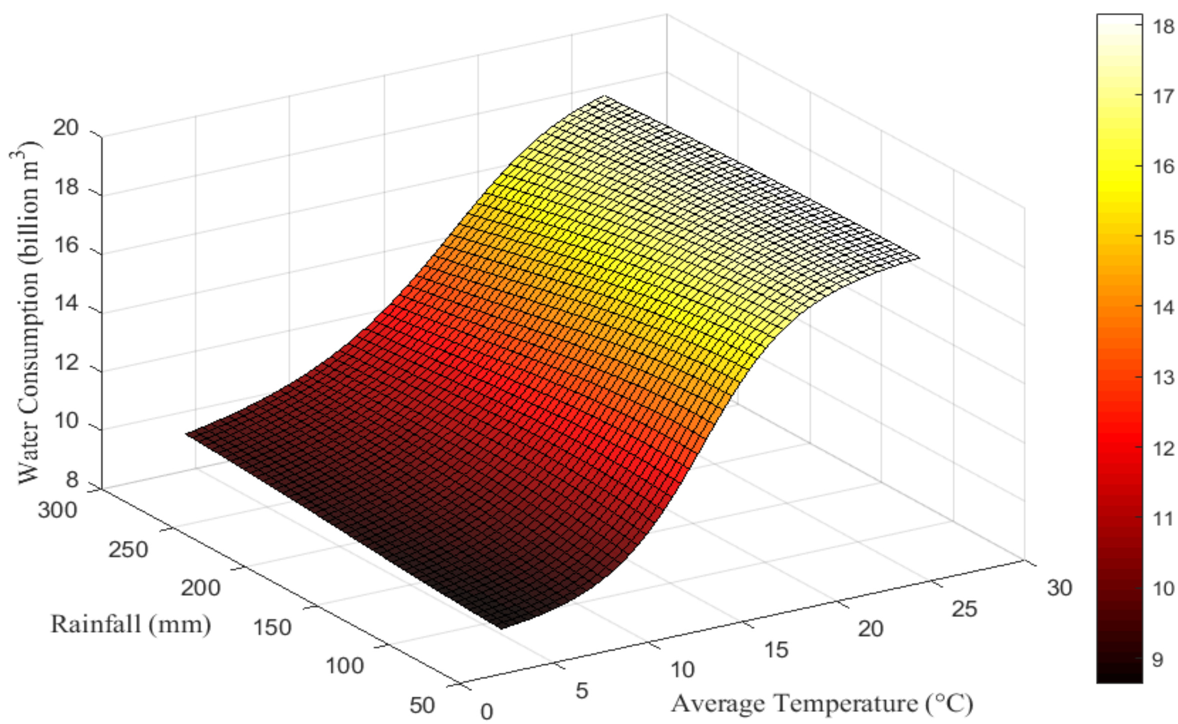

Figure 3. Predicted water consumption trends and the influence of climate factors in Zhejiang Province.

Corresponding to the model training, noticeable peaks in water consumption were observed during the hotter summers of 2017, 2018, and 2019. Elevated temperatures amplify evapotranspiration rates stemming from agricultural and domestic practices, consequently intensifying water demand. Moreover, warmer conditions significantly elevate crop water requirements to sustain optimal yields. Relatively diminished rainfall during these years necessitated augmented irrigation withdrawals to compensate for the shortfall in precipitation. These findings substantiate the influence of climate patterns on the observed water consumption patterns during the model training. Conversely, the decline in water consumption in 2020 coincides with a relatively cooler and wetter summer period.

4.3 Energy Consumption Prediction

The predicted values for energy consumption, based on inputs of average temperature and rainfall, are presented in Figure 4. Over the period from 2017 to 2022, energy usage followed an increasing trajectory, with average annual consumption rising from approximately 2,580 million tons of standard coal in the initial year to over 3,060 million tons in 2022.

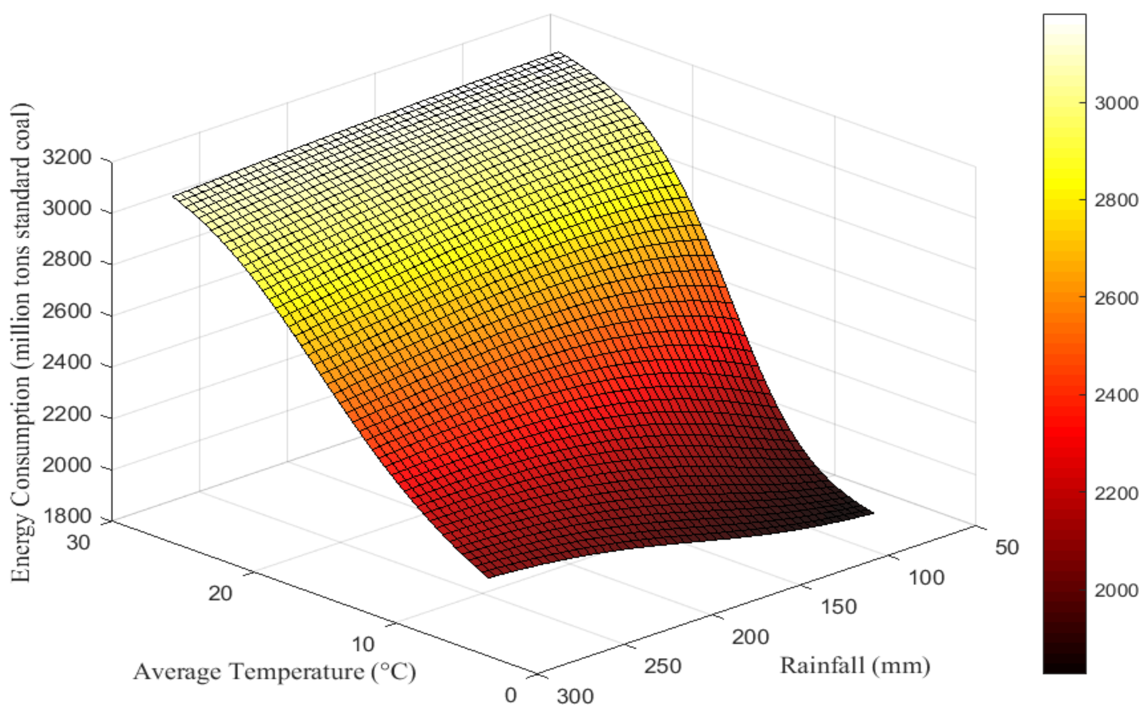

Figure 4. Predicted energy consumption trends and the influence of climate factors using ANN modeling.

Peaks in observed energy consumption coincided with hotter summers in 2017, 2018, and 2019. Higher temperatures increased the demand for cooling, leading to elevated electricity usage (. Furthermore, higher average temperatures during these years coincided with peak agricultural activities such as irrigation, requiring additional fuel for water pumping. Comparatively lower rainfall necessitated supplementary irrigation withdrawals, involving additional energy consumption.

4.4 Logistics Efficiency Prediction

The predicted values for logistics efficiency, obtained through the implementation of ANN, are presented in Figure 5. From 2017 to 2022, logistics efficiency generally exhibited an increasing trend, with average annual efficiency rising from approximately 7.3 tons/10,000 yuan in 2017 to 7.8 tons/10,000 yuan in 2022.

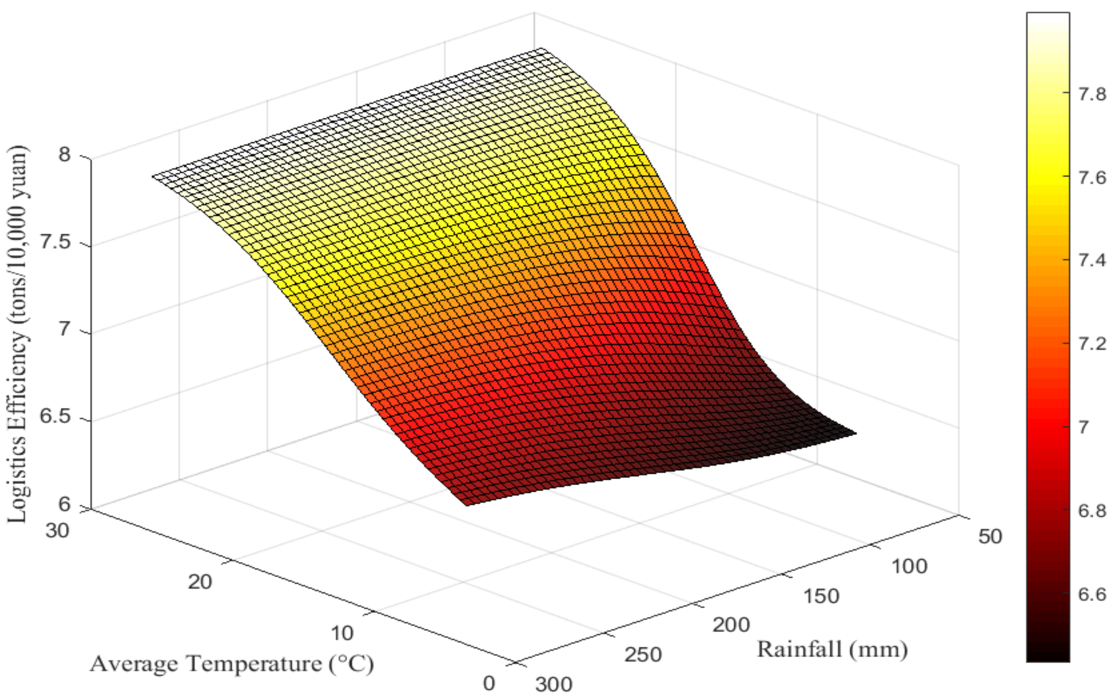

Figure 5. Predicted trends in logistics efficiency using ANN and the impact of climate factors including average temperature and rainfall.

Peaks in observed logistics efficiency coincided with hotter summers in 2017, 2018, and 2019. Higher temperatures led to reduced cargo handling times through accelerated commodity preservation and processing. Warmer conditions also increased infrastructure utilization, particularly in activities like transportation of construction materials. These findings substantiate the influence of climate on logistics performance, as demonstrated in the model training. The decrease in logistics efficiency observed in 2020 aligns with a relatively cooler and wetter summer, resulting in reduced overall demands. Analyzing logistics efficiency at the seasonal level offers further insights. Spring temperatures facilitate construction and resupply logistics, while summer peaks indicate the transportation of agricultural products. Autumn demands signify movements associated with post-harvest processing, whereas winter utilization centers around primary infrastructure maintenance.

4.5 Economic Growth Prediction

The predicted values for GDP, obtained through the implementation of using actual outputs recorded in Table 1, are presented in Figure 6. Over the study period, GDP exhibited an overall increasing trajectory, growing from approximately RMB 12,235 billion in 2017 to RMB 13,780 billion in 2022, reflecting the broader trends of socioeconomic advancement in China.

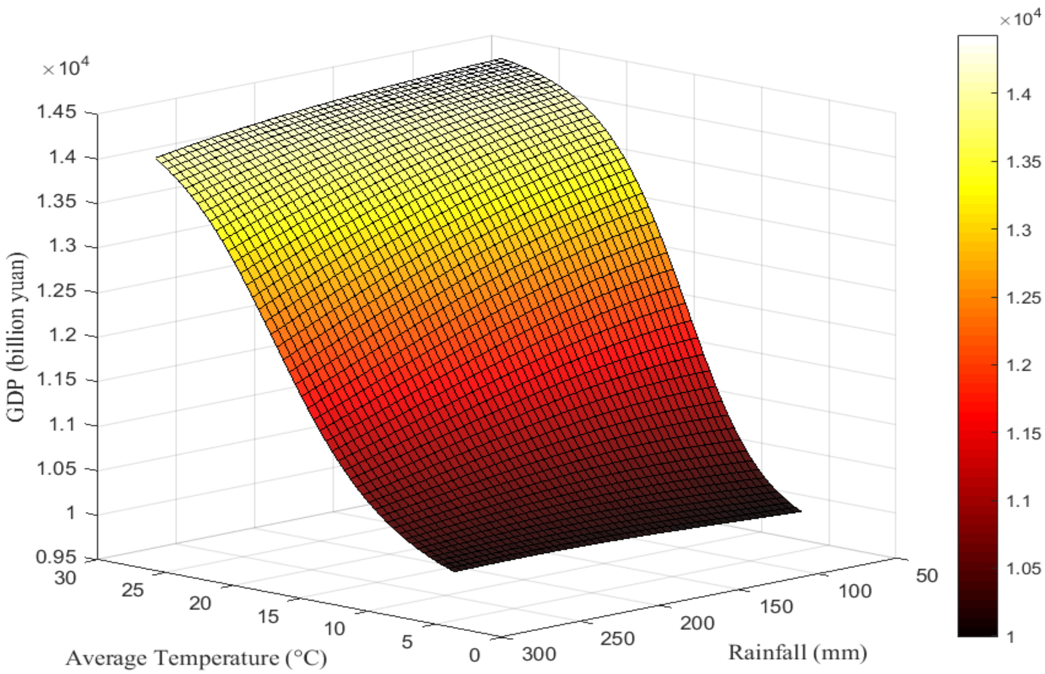

Figure 6. Predicted GDP trends using ANN and the influence of climate factors in Zhejiang Province.

The peak period of infrastructure construction in this timeframe capitalized on elevated temperatures to expedite the development process. Moreover, summer represents a prominent tourist season in Zhejiang, thereby contributing to the service sector's influence on the region's GDP. However, excessively high temperatures can potentially hamper labor productivity and result in crop and infrastructure damage if the implementation of adequate adaptation measures is lacking.

Seasonally, the increments in spring GDP reflected increased agricultural outputs with elevated planting temperatures, while summer peaks represented combined contributions from multiple climate-sensitive sectors, including agriculture, construction, tourism, and industry.

4.6 Performance of ANN Model

The goodness-of-fit is measured using the coefficient of determination (R^2), ranging from 0 to 1, where values closer to 1 indicate higher correlation and predictive strength. Figure 7 illustrates the linear regression analysis between predicted and observed crop yield values from 2017 to 2022, demonstrating an exceptionally high R^2 value of 0.9964.

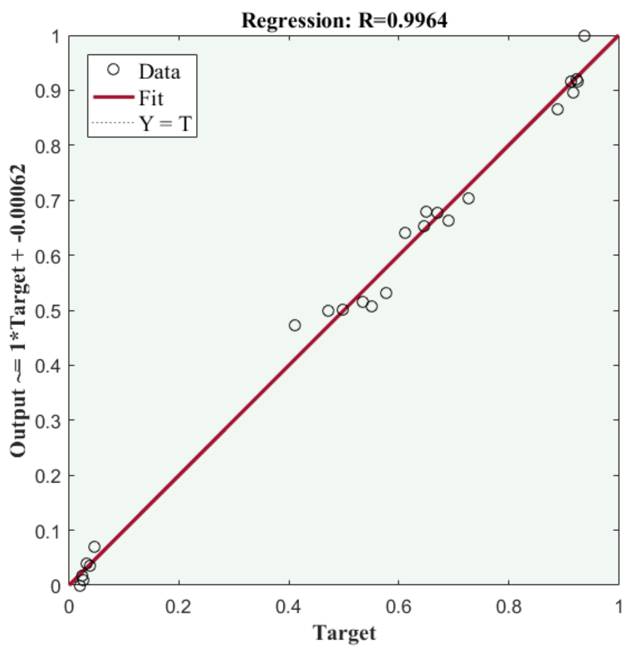

Figure 7. Analysis of predicted vs. actual crop yield outputs using linear regression.

Similarly, Figure 8 presents the linear regression diagram for water consumption, yielding an excellent R^2 value of 0.99585. This high coefficient signifies the model's ability to accurately mimic water usage patterns influenced by climatic drivers over different time periods.

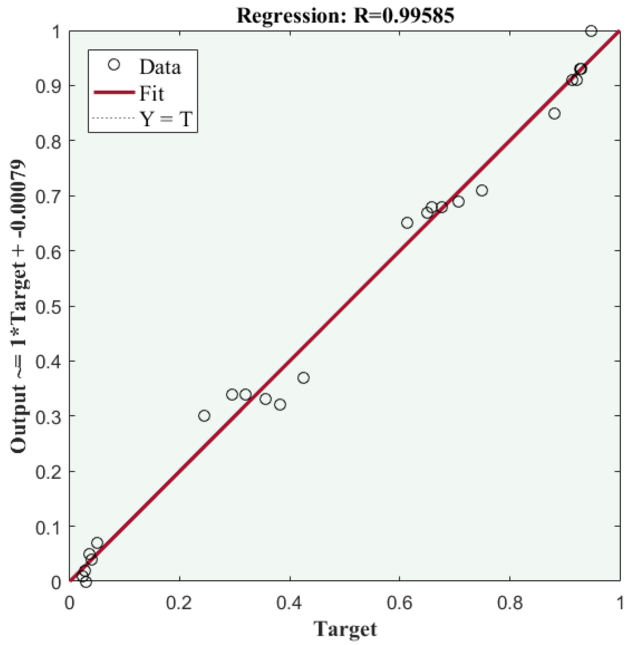

Figure 8. Linear regression analysis of predicted vs. actual water consumption.

Moving to the energy sector outputs, Figure 9 showcases the linear regression plot for energy consumption, with an R^2 value of 0.99508.

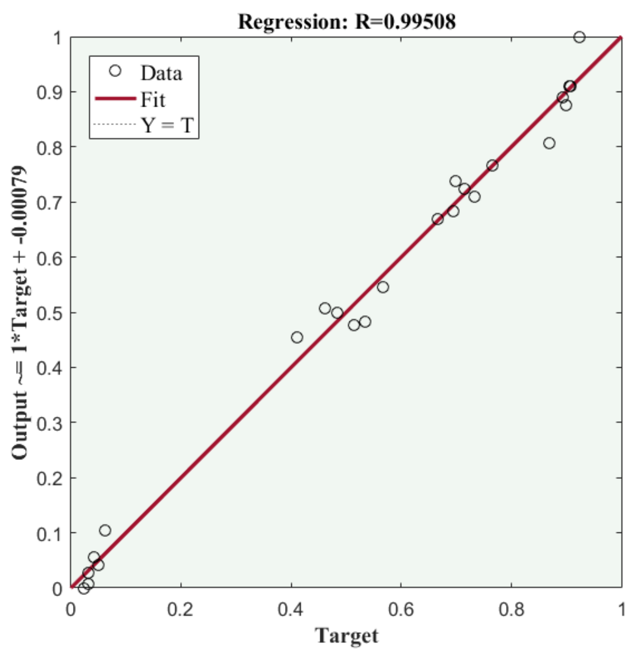

Figure 9. Linear regression analysis of energy consumption predictions.

Next, Figure 10 depicts the regression analysis between predicted and observed logistics efficiency values. With an R^2 value of 0.97883, the optimized ANN demonstrates reasonable predictions of logistical performance based on climatic conditions.

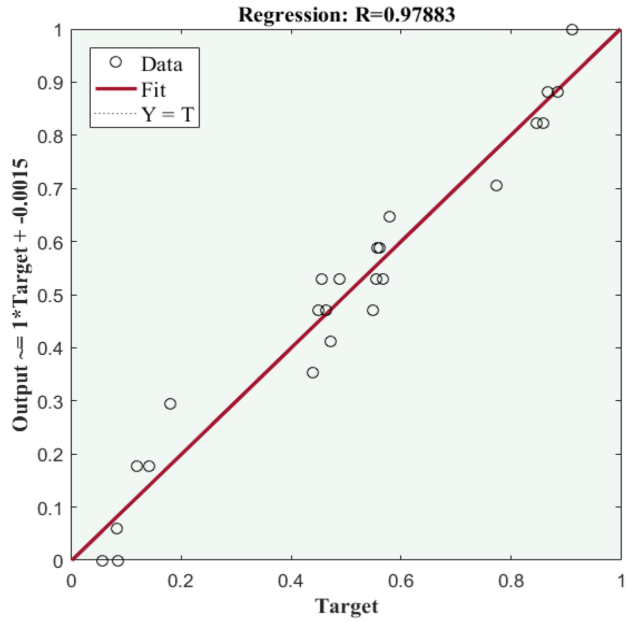

Figure 10. Linear fit between predicted and observed logistics efficiency outputs.

Lastly, Figure 11 portrays the linear regression evaluation for GDP, with an R^2 value of 0.98987. This attests to the model's proficiency in tracking annual GDP trends, indirectly influenced by temperature and precipitation that affect sensitive sectors such as agriculture and construction.

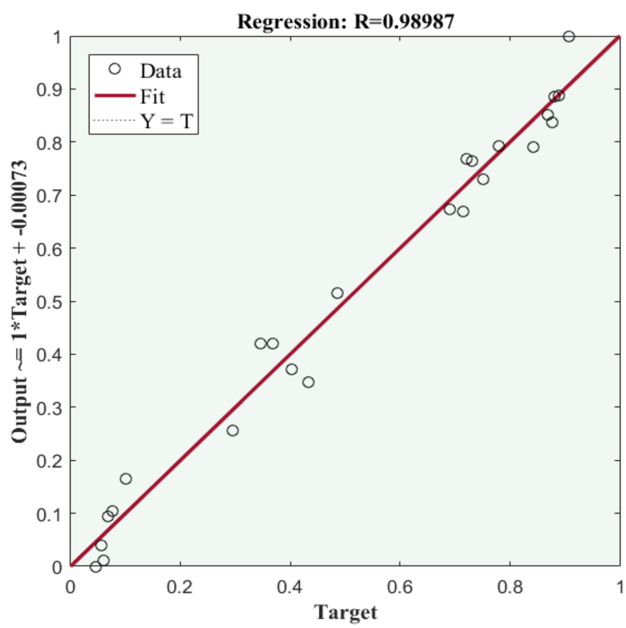

Figure 11. Regression analysis assessing economic growth forecasting (GDP).

5. Conclusions

This study successfully developed an optimized feedforward artificial neural network (ANN) model to examine the complex connections between climatic factors and key agricultural-economic outputs in Zhejiang Province, China. By analyzing temperature and rainfall inputs, the model accurately predicted outputs related to crop yield, water consumption, energy usage, logistics efficiency, and economic growth on both annual and seasonal scales. The high coefficient of determination (R2) values exceeding 0.97 between predicted and actual outputs validated the effectiveness of the trained ANN structure in capturing the nonlinear relationships in the input-output datasets. The annual predictions revealed fluctuations in outputs that corresponded to observed climatic anomalies, with peaks in yield, water consumption, energy usage, and economic growth during warmer summers and declines during cooler conditions. Seasonal predictions further highlighted variations in climatic drivers across different growing cycles. The analysis of individual output predictions identified valuable linkages between climate and specific activities, such as progressive agricultural practices, the need for sustainable water management, the urgency of transitioning to clean energy sources, and opportunities for seasonal infrastructure optimization. These findings emphasized the importance of considering temporal granularity in understanding the interdependencies among different sectors and provided valuable insights to inform evidence-based strategies for rural development.

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